Remote Sensing Applications: Society and Environment 37 (2025) 101404

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Assessing drivers of vegetation fire occurrence in Zimbabwe - Insights from Maxent modelling and historical data analysis

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ARTICLE INFO

Keywords:
Fire risk
Maxent
MODIS
Probability
Vulnerability
Zimbabwe

ABSTRACT

Vegetation fires are known to profoundly impact ecosystem structure and composition, posing threats to ecosystem stability and human safety. In Zimbabwe, uncontrolled fires have been recurrent, yet a rigorous analysis of the key drivers is still lacking. Previous studies in Zimbabwe have predominantly focused on spatio-temporal dynamics of the occurrence of vegetation fire, leaving a gap in understanding the underlying drivers. Accurate prediction of fire occurrence and identification of the major drivers is imperative for effective fire management strategies. The study employs the Maxent model, a machine-learning approach, to analyze historical MODIS fire data alongside bioclimatic, topographic, anthropogenic, and vegetation variables, to assess the likelihood of fire occurrence in Zimbabwe. The research also aims to elucidate the major factors that influence fire occurrence within the region. The independent contributions of predictor variables to the model's goodness of fit are evaluated using a jackknife test, while model accuracy is assessed using the AUC (area under the receiver operating characteristic curve). Results indicate that elevation, precipitation seasonality, temperature annual range and human footprint emerge as the major factors influencing fire occurrence in Zimbabwe. The model demonstrates an acceptable accuracy, with an average AUC of 0.77. This study underscores the utility of the Maxent model in elucidating the contributions of various environmental factors to vegetation fire occurrence. Moreover, the ability of the model to predict the probability of fire occurrence offers valuable insights for fire managers, facilitating the assessment of the spatial vulnerability of vegetation to fire occurrence. Overall, this research contributes to an improved understanding of the drivers of vegetation fires in Zimbabwe and provides a practical tool for enhancing fire management efforts in the region and beyond.

1. Introduction

Although the occurrence of vegetation fires has greatly shaped the savanna ecosystem, fires are a major disturbing factor in global forest ecosystems, contributing to land degradation (Global Forest Watch, 2023). Although many prevention and mitigation strategies have been put in place, fires remain a major global concern, degrading forested areas (Armenteras et al., 2017; Mishra et al., 2023) and disturbing biodiversity and ecosystem services (Piralilou et al., 2022; Zhang et al., 2017). Additionally, fires significantly contribute to

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https://doi.org/10.1016/j.rsase.2024.101404
Received 6 August 2024; Received in revised form 13 October 2024; Accepted 18 November 2024
Available online 19 November 2024

greenhouse gas emissions, hence, becoming an important contributor to global climate change, which in turn influences the increase in fire occurrence incidents and their severity (Mishra et al., 2023; Wasserman and Mueller, 2023). Uncontrolled fires can be major disasters and have devastating effects on human lives and may lead to economic losses (Zhang et al., 2017).

Effective fire management greatly depends on a deep understanding of the dynamic spatiotemporal distribution of fires and the factors driving their occurrence in a landscape. Variability in the spatiotemporal distribution of vegetation fire occurrence is greatly controlled by several factors including fuel type, topography, precipitation and temperature (Zhang et al., 2017). Additionally, anthropogenic factors are also important predictors of fire occurrence. Topography influences the local climatic variations, especially the spatial distribution of precipitation and temperature, hence, controlling fuel type distribution and flammability (Zhang et al., 2017). Temperature and precipitation control fire occurrence by determining fuel availability and moisture (Graham et al., 2023). For instance, higher precipitation and temperature conditions increase the probability of fire occurrence (Archibald et al., 2010a).

Despite being highly accurate, traditional methods of collecting fire data in a landscape, such as mapping burned areas using handheld GPS receivers, have proven to be expensive, labour-intensive, time-consuming and difficult to carry out, especially over large and inaccessible areas (Wang et al., 2023). Earth observation and geospatial methods have proven to offer practical and cheap means to predict and quantify the occurrence of fires both locally and globally. Satellite-borne sensors are widely used in fire monitoring studies, and they greatly utilize the thermal, shortwave, mid-infrared, and visible parts of the electromagnetic spectrum. Fire detection sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS), for example, utilize the brightness temperature in the fire detection algorithm. The free availability of remotely sensed data has allowed the easy generation of topographic derivatives such as aspect and slope, from digital elevation models (DEM). Rainfall and temperature data are also freely available from databases such as the WorldClim which provides bioclimatic data (Fick and Hijmans, 2017). The modelling of fire occurrence with limited ground observations greatly benefits from the availability of satellite-derived variables (Odebiri et al., 2020).

Globally, several studies have been done to assess the spatiotemporal occurrence of fires in differing ecosystems (Guo et al., 2017; Mishra et al., 2023; Oliveira, 2021). In Southern Africa, a few studies (Makhaya et al., 2022; Mishra et al., 2023; Mpakairi et al., 2018) have utilized spatial techniques to determine the factors that drive fire occurrence. For instance, Makhaya et al. (2022), utilized topographic and bioclimatic variables to assess key drivers supporting the occurrence of vegetation fires in Ethekwini Municipality, KwaZulu Natal, South Africa. Studies carried out in Zimbabwe mainly focused on the spatial and temporal occurrence of fires (Mpakairi et al., 2018; Mupfiga et al., 2022; Shekede et al., 2021; Mupfiga et al., 2024) and the influence of tenure systems on areas burned (Maponga et al., 2018). Although the previous studies provided valuable information on fire occurrence using various methods, the main influential environmental and human-related factors which influence the occurrence of vegetation fires in Zimbabwe are still poorly understood. While Mpakairi et al., 2018 predicted the occurrence of vegetation fires as a function of factors such as elevation, air temperature, biomass and population density in a protected area in Zimbabwe, the study was done on a small scale. The current study analyzed the key environmental and anthropogenic factors that influence the occurrence of vegetation fires within the study area. The current study includes a more diverse set of environmental variables, incorporating the human footprint variable, a more robust indicator for anthropogenic effect on fire occurrence and at a larger scale. The study presents new information on predicting the likelihood of vegetation fire occurrence within a landscape.

In the past few decades, a high number of cases of vegetation fires have been experienced in Zimbabwe despite the availability of several legislative frameworks (Mupfiga et al., 2022; Shekede et al., 2021, 2024). The temperature rise, the fall in precipitation levels and the recurrence of vegetation fires clearly show the reality of climate change (Mupfiga et al., 2022; Mushore et al., 2021). This study focused on a nationwide analysis of the factors driving the spatiotemporal occurrence of vegetation fires in Zimbabwe, Southern Africa. The study covers a larger area, characterized by diverse climatic, topographic, vegetation, and anthropogenic conditions. The nationwide approach employed in this study offers a wall-to-wall analysis of the predictor variables that drive the occurrence of vegetation fires in Zimbabwe. To fill the research gap, this study employed the Maximum Entropy model (Maxent), a widely used species distribution model, in predicting the likelihood of vegetation fire occurrence across the landscape and assessing the relative contribution of the factors to the spatial occurrence of vegetation fires.

The results from the study are important for informed fire management decisions to minimize the impacts of fire. The identification of major drivers that influence the occurrence of vegetation fires and prediction of the likelihood of fire occurrence assists in providing a framework for proactive measures for the reduction of the risk of fire occurrence thereby contributing to the formulation of effective strategies for the prevention and management of vegetation fires. The findings from the study avail valuable insights which assist decisions towards national fire prevention and mitigation strategies.

2. Materials and methods

2.1. The study area characteristics

This national scale study covered Zimbabwe (Fig. 1), a country situated in Sub-Saharan Africa between 15°30″ to 22°30″ S and 25°30″ to 33°30″ E, covering an area of about 390,757 km^2. Zimbabwe is characterized by topography which varies from below 167 m in southern parts to just above 2000 m in Eastern regions. Annual rainfall in Zimbabwe decreases from agroecological zone I to zone Vb with temperatures increasing from zone I to Vb. Most of the precipitation which varies spatially in Zimbabwe, falls during summer from late Nov to April. There is variation in temperature along elevation zones. Being a savanna ecosystem, fire frequently occurs in the study area and contributes to deforestation and land degradation (Global Forest Watch, 2023). About 95% of forest cover in Zimbabwe is characterized by savanna woodlands with a fire season generally occurring from around August to October (Archibald et al., 2010b; Mupfiga et al., 2022).

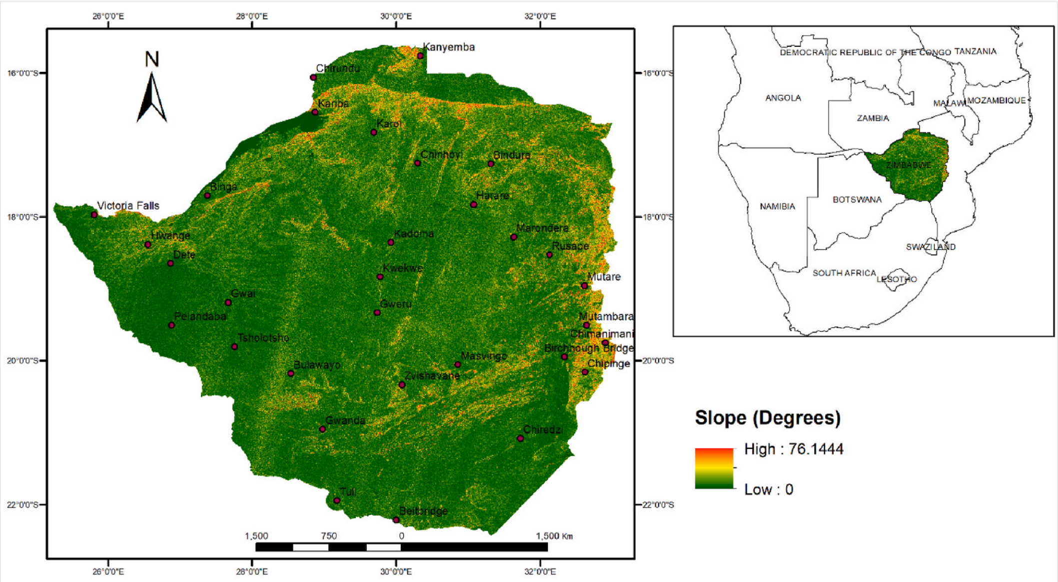

Fig. 1. Map of the topographic characteristics (slope) which was used to model vegetation fire vulnerability in Zimbabwe.

2.2. Data

2.2.1. Dependent variables: fire occurrence data

Due to the unavailability of historic field data on fires, MODIS Collection 6 fire data (January to December 2018) was used. The MODIS fire data product (MCD14ML), is recognized as one of the most accurate and effective satellite data systems for fire monitoring (Graham et al., 2023; Justice et al., 2011; Zhang et al., 2017) and was used in several fire occurrence studies (Mishra et al., 2023; Mupfiga et al., 2022; Zhang et al., 2017). The presence of a thermal band within the MODIS, specifically developed for fire monitoring, makes the MODIS data the most suitable dataset for fire monitoring studies. The fire data which was acquired from the Fire Information for Resource Management System (FIRMS) platform (https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data) (accessed on 4 March 2023), includes information on the location, the time and the date when the fire data was acquired, the confidence level and the brightness of the fire. The MODIS algorithm identifies pixels containing fires that are actively burning during the satellite's overpass (Giglio et al., 2018; Justice et al., 2011). Only fires occurring within vegetated areas and with confidence levels higher than 30% were utilized in the analysis.

2.2.2. Predictor variables

The variables used in the analysis included topographical, climatic, vegetation and anthropogenic, which are the common factors influencing the spatiotemporal distribution of vegetation fires (Graham et al., 2023; Makhaya et al., 2022; Mishra et al., 2023).

2.2.2.1. Bioclimatic variables. The probability of fire occurrence largely depends on climatic conditions which influence the availability of fuel load and moisture and determine the level of fire fuel such as forest litter, grasses, and leaves. Long-term dry conditions influence the drying of fuels thereby increasing the susceptibility of vegetation to burning. Warmer temperatures between 20 °C and 27 °C result in the drying of fuels in the savanna, thereby increasing the likelihood of fire ignition. Similarly, precipitation influences the amount of moisture available for vegetation growth and eventually determines the amount of dry-season biomass that will be available for burning (Archibald et al., 2010a).

The study considered 19 bioclimatic variables (1 km spatial resolution), freely extracted from https://www.worldclim.org/data/bioclim.html (accessed on 28 April 2023). Detailed information on the development of the bioclimatic data is found in Fick and Hijmans (2017) and listed in Table 1. The bioclimatic variables, computed from long-term rainfall and temperature averages, were preferably used in this study compared to raw monthly rainfall and temperature data because they were fine-tuned into more ecologically meaningful variables (Moyo et al., 2019). These 19 variables, which show the annual and seasonal temperature and precipitation, have been successfully used in other studies globally (Makhaya et al., 2022; Mishra et al., 2023) as governing factors for fire occurrence.

2.2.2.2. Topographic variables. Elevation, slope, and aspect greatly determine the local climatic variations, especially the spatial distribution of precipitation and temperature, controlling fuel type distribution and flammability (Graham et al., 2023; Zhang et al., 2017). The digital elevation model (DEM) utilized in the analysis was extracted from the Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) and downloaded from the www.usgs.gov platform at 30m spatial resolution. The aspect and slope

Table 1
Predictor variables which were used for modelling fire occurrence.

Variable		Source
Bioclimatic	Annual mean temperature (Bio1) Mean monthly temperature range (Bio2) Isothermality (Bio3) Temperature seasonality (Bio4) Maximum temperature of warmest month (Bio5) Mean temperature of coldest month (Bio6) Temperature annual range (Bio7) Mean temperature of wettest quarter (Bio8) Mean temperature of driest quarter (Bio9) Mean temperature of warmest quarter (Bio10) Mean temperature of coldest quarter (Bio11) Annual precipitation (Bio12) Precipitation of wettest month (Bio13) Precipitation of driest month (Bio14) Precipitation seasonality (Bio15) Precipitation of wettest quarter (Bio16) Precipitation of driest quarter (Bio17) Precipitation of warmest quarter (Bio18) Precipitation of coldest quarter (Bio19)	https://www.worldclim.org/data/worldclim21.html (Fick and Hijmans, 2017)
Vegetation	NDVI	
Topographic	Elevation Slope Aspect	https://www.worldclim.org/data/worldclim21.html (accessed 15 September 2023) Fick and Hijmans (2017)
Anthropogenic	Human footprint map	https://sedac.ciesin.columbia.edu/data/set/wildareas-v2-human-footprint-ighp/data-download (accessed 15 September 2023) Venter et al. (2016)

variables were derived from the DEM in ArcGIS 10.5 using the Spatial analyst tool. The topographic variables were resampled to 1 km spatial resolution to match the fire data and other predictor variables.

2.2.2.3. Fuel variables. Due to variability in combustibility and fuel load characteristics, vegetation types are affected differently by fire. Some specific land cover types such as shrubs and conifers tend to be more fire-prone than other land cover types such as wetlands, burned areas, and agricultural areas (Adab et al., 2018). Vegetation flammability is greatly influenced by its moisture content and structure which affect fuel load. Vegetation which is generally dry, woody, and has higher oil content tends to be more flammable compared to other vegetation types. On the other hand, succulent vegetation, with higher moisture content and less litter is less flammable. The highest probability of fire occurrence is associated with high NDVI values ranging from 0.5 to 1 (Mpakairi et al., 2018). The MODIS NDVI product was used in this study as a proxy for biomass and representing the fuel variable.

2.2.2.4. Anthropogenic variables. There is a close relationship between the occurrence of fire and the presence of humans and their activities. Human activities increase the probability of fire occurrence by providing possible sources of fire ignition (Zhang et al., 2017). The susceptibility to fire occurrence tends to increase with proximity to populated settlements and accessibility of forests to roads (Armenteras et al., 2013; Guo et al., 2017; Piralilou et al., 2022). The human footprint map, developed by Venter et al. (2016) was used as a proxy for the environmental disturbance caused by human pressures. This anthropogenic data set was developed based on overlaying of eight anthropogenic factors, population density, built-up area, croplands, pasture land, roads, railways, navigable waterways and electric infrastructure. The details of the variables used in the modelling are given in Table 1.

2.3. Data preparation

The processes done on the collected data are clearly shown in Fig. 2. The study area map was used to clip the topographic, human footprint, NDVI, bioclimatic and fire data using the spatial analyst tool in ArcMap. After the predictor variables, in raster format, were stacked in R Studio, the fire data was used to extract raster values for each fire point. The values of the predictor variables for each fire point were recorded in a Microsoft Excel csv file.

2.4. Selection of predictor variables

Multicollinearity is detected when two or more predictor variables are highly correlated and negatively affect models. To avoid instability in the Maxent model's performance, testing for multicollinearity among the predictor variables was done in this study using the variance inflation factor (VIF) in R Studio. The non-correlated predictor variables used in the Maxent model were chosen based on the value of the variance inflation factor (VIF) where highly correlated variables with VIF eliminate the highly correlated predictor variables. The collinearity matrix in Fig. 3 shows the correlation interaction of the predictor variables considered for the prediction of

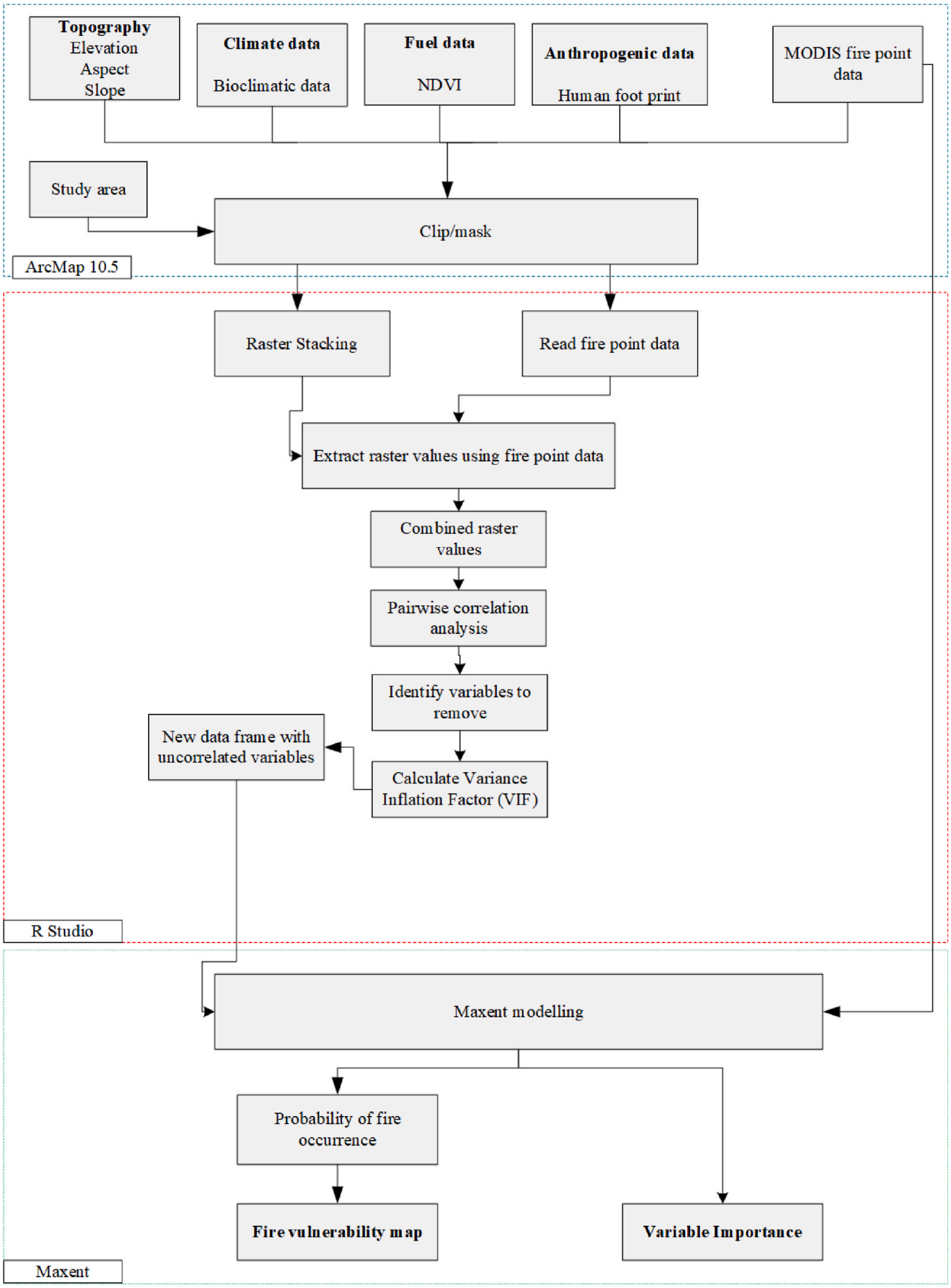

Fig. 2. Flow diagram showing the processing of data used in modelling vegetation fire vulnerability of Zimbabwe.

fire occurrence in Zimbabwe. The predictor variables with VIF less than 10 (Dormann et al., 2013; Makori, 2022) were selected for predicting fire occurrence using Maxent (version 3.3.3).

2.5. Modeling the likelihood of fire occurrence

The probability of fire occurrence was predicted using the Maxent model (Phillips et al., 2006) as a function of topographic,

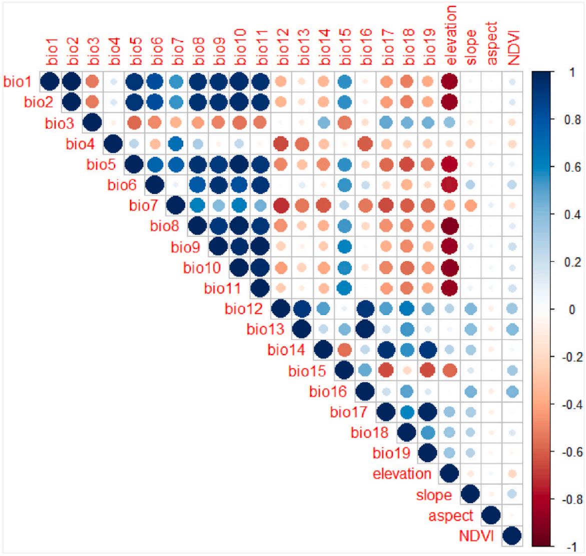

Fig. 3. The collinearity matrix showing the correlation interaction of the predictor variables used to model fire occurrence in Zimbabwe.

climatic, anthropogenic and vegetation factors. Maxent is a machine learning model broadly applied in suitability and ecology studies. It correlates explanatory variables with the locations of species presence to predict suitability (Fitzgibbon et al., 2022). The model utilizes presence-only data together with raster covariates to predict the suitability of a specific phenomenon and calculates the probability of occurrence ranging from 0 to 1 (Adab et al., 2018). Modelling the suitability of the occurrence of a phenomenon using Maxent does not require verification of the absence-only data which is usually difficult to acquire (Adab et al., 2018). In this study, the MODIS presence-only active fire data was utilized as the dependent variable in modelling the likelihood of fire occurrence using the Maxent model. The contribution of each predictor variable to the model results was determined using the jackknife tool within the Maxent 3.3.3. The Maxent model runs several repetitions until there are no further changes in the spatial estimation of the probability of fire occurrence and identifies the maximum likelihood of fire occurrences within the study area (Rahmati et al., 2016). For this study, a map showing the fire risk level was developed by reclassifying the map showing the probability of fire occurrence into 4 classes very low risk (0–0.25), low risk (0.25–0.5), high risk (0.5–0.75), and very high risk (0.75–1) (Chen et al., 2015).

For best model results, the calibration of the model is essential. In the Maxent model, fire data was divided into training (70%), for building the model and test datasets (30%), for the validation of the model (Odebiri et al., 2020; Phillips et al., 2006) using the random test percentage setting. The model was run using the default Maxent settings. To check for overfitting, the difference between values of the training area and the test area under curve (AUC) was assessed. Since overfitting was not detected, the default regularization was utilized in the model. To generate a map showing the likelihood of fire occurrence in Zimbabwe, the 10-percentile limit was utilized in the Maxent model. The threshold assumed that the omission error of the occurrence is less than 10%, and 90% of the fire data was modelled as present (Odebiri et al., 2020).

The Maxent model produces the receiver operating characteristic (ROC) curve as output which gives an area under curve (AUC) as a measure of the model accuracy. The receiver operating characteristic (ROC) curve, which describes the model performance (Rahmati et al., 2016), was utilized to evaluate and validate the Maxent model. It shows the probability that fire occurrence (sensitivity) is correctly explained by the predictor variables as compared to the absence (specificity) of fire occurrence. It is generated through the plotting of sensitivity on the y-axis against specificity on the x-axis. For highly accurate models, the AUC value will be close or equal to 1, while, a model performing no better than random will have a value less than or equal to 0.5 (Phillips et al., 2006). The ROC curve has been widely used in several previous studies for the evaluation and validation of probability modelling (Makhaya et al., 2022; Mishra et al., 2023; Odebiri et al., 2020).

3. Research findings

3.1. Selection of the predictor variables

Multicollinearity test results given in the form of the variance inflation factor (VIF) of the non-collinear predictor variables are shown in Table 2. As indicated in Table 2, 11 out of 23 predictor variables had VIF values less than 10, implying that they had a low degree of correlation and were therefore selected to be used in the Maxent model. This makes the predictor variables listed in Table 2 the best subset for use in predicting the spatial variability of fire occurrence using Maxent.

Table 2
The VIF value for the selected predictor variable used in the Maxent model.

Predictor Variables	VIF
Annual mean temperature (Bio1)	6.5
Isothermality (Bio3)	1.9
Temperature seasonality (Bio4)	3.0
Temperature annual range (Bio7)	5.4
Precipitation seasonality (Bio15)	2.2
Precipitation of warmest quarter (Bio18)	2.1
Elevation	5.0
Aspect	1.0
NDVI	1.2
Human footprint	1.0
Slope	1.5

3.2. Maxent model

3.2.1. Analysis of Maxent model results

Fig. 4a shows that the omission on test samples (turquoise) is close to the predicted omission rate (black) signifying a good Maxent model. Based on the AUC value of 0.77 (Fig. 4b), the Maxent model can be said to have performed better in predicting fire occurrence than a random model (Jiang et al., 2018).

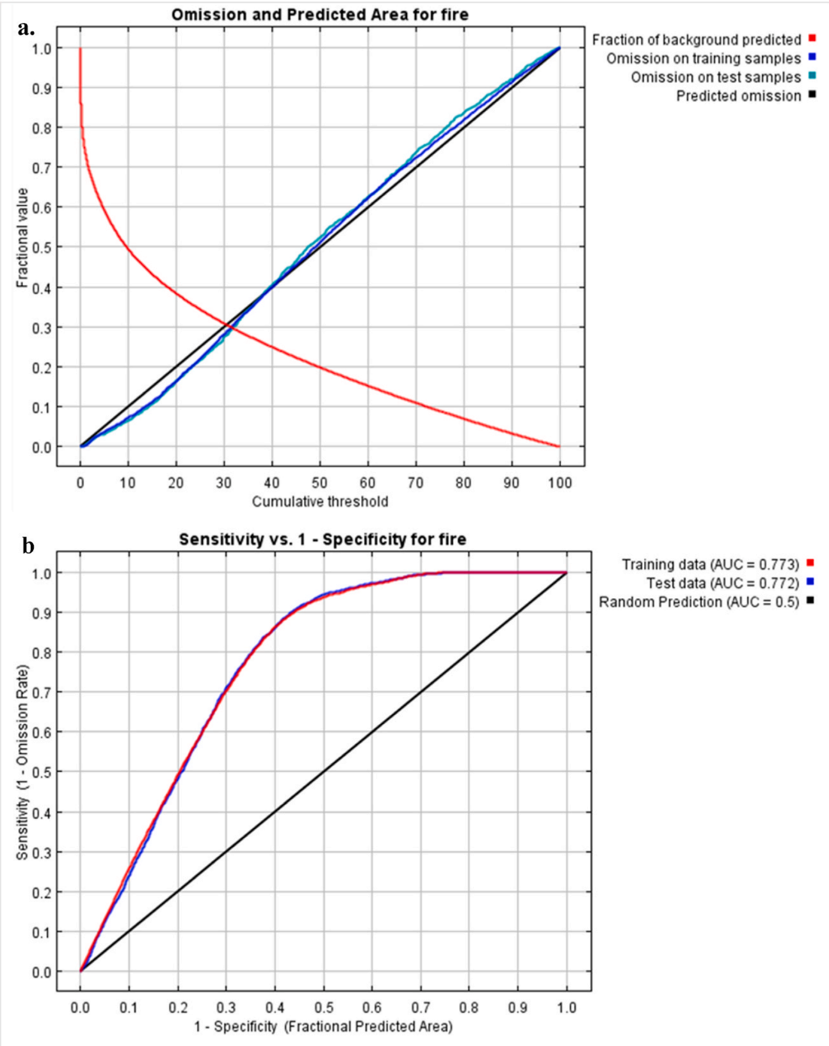

Fig. 4. a. The omission analysis of the test and training data sets for the Maxent model. **b.** The ROC curve for training and test data sets as shown by AUC.

3.2.2. Analysis of variable contributions

The Maxent model allows for the assessment of each variable's influence on the model results. The higher percentage contribution of any predictor variable implies that it has a higher effect on the prediction of the likelihood of the occurrence of vegetation fires. The ranking of the estimated relative contributions of the variables towards the prediction of fire occurrence is shown in Table 3. Predictor variables with higher values tend to present greater importance in model prediction.

Table 3 shows that the predictor variable with the highest percentage contribution (31.5%) towards the occurrence of vegetation fires in Zimbabwe is elevation followed by temperature annual range (Bio7) (26.5%). The human footprint and precipitation seasonality (Bio 15) also had a considerable predictive contribution to fire occurrence with percentage contributions of 16.4% and 13.9% respectively. The total contribution of elevation, temperature annual range, human footprint and precipitation seasonality (Bio 15) to fire occurrence was over 88%. Variables like slope, aspect and isothermality (Bio 3) had very low contribution to fire occurrence in Zimbabwe as shown in Table 3.

Findings from the assessment of the contribution of predictor variables towards the occurrence of vegetation fires using Maxent's jackknife test are shown in Fig. 5. The bars in turquoise colour reveal the Maxent model's overall accuracy excluding the individual predictor variable. On the other hand, the blue bars illustrate the individual predictor variable's performance and accuracy if applied in isolation. The model's overall gain, calculated when all the predictor variables are used, is shown by the red bar.

Fig. 5 shows that when applied alone, the annual mean temperature (Bio 1) variable, has the highest gain implying that this predictor variable contains the most important information which is independent of the other variables. Temperature annual range (Bio 7) is the predictor variable which caused the reduction of the model's overall gain if it is excluded. This, therefore, implies that the 'temperature annual range' variable contains more information which is absent in the other variables.

3.2.3. Spatial distribution of fire risk

The map in Fig. 6 showing the spatial distribution of fire occurrence in Zimbabwe was generated from the Maxent prediction model. The map shows the probability of fire occurrence, reclassified into fire risk levels, based on MODIS fire points as a function of bioclimatic, topographic, fuel and anthropogenic factors as predictor variables. As shown in Fig. 6, areas with a very high probability of fire occurrence are presented in red colour, while areas with a very low likelihood of fire occurrence are shown in dark green. Areas of low and high risk of fire occurrence are shown in light green and orange colours, respectively. The areas characterized by a high to very high probability of fire occurrence cover more than 50% of Zimbabwe.

Table 3
The percentage contribution of the variables towards fire occurrence modelled using the Maxent model.

Predictor variables	Percentage contribution (%)
Elevation	31.2
Temperature annual range (Bio7)	26.5
Human footprint	16.4
Precipitation seasonality (Bio15)	13.9
Precipitation of warmest quarter (Bio18)	6.6
NDVI	2.6
Temperature seasonality (Bio4)	1.8
Isothermality (Bio3)	0.5
Slope	0.3
Aspect	0.1

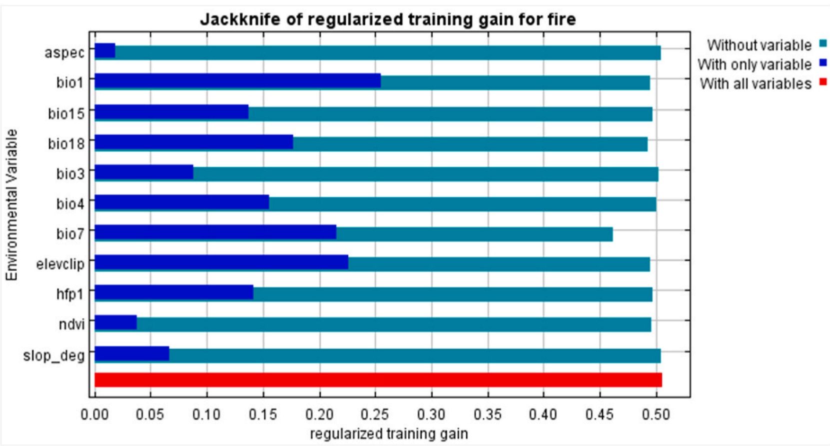

Fig. 5. The results of the analysis variable importance using the jackknife test.

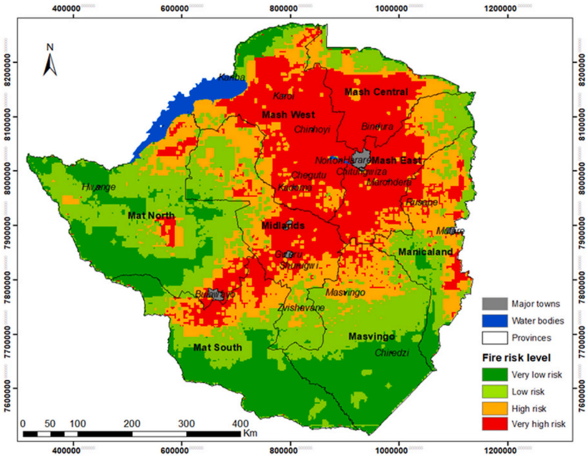

Fig. 6. A map showing the predicted fire occurrence risk level for each province in Zimbabwe. The two metropolitan provinces (Harare and Bulawayo) and other major towns were masked as these are mostly urban areas.

Based on the Maxent probability model results, the very high risk of fire occurrence characterizes the central, northern and eastern regions which generally include the Mashonaland west, east and central provinces of Zimbabwe as shown in Figs. 6 and 7. Fig. 7 clearly shows the percentage area covered by the predicted fire risk levels for each province in Zimbabwe where 63% of the area covered by Mashonaland West province falls within the very high fire risk zone. The southern regions and some western parts characterized by the low-lying areas of Gonarezhou (Masvingo province) and parts of Hwange (Matebeleland North province) National Parks, respectively, had over 40% area characterized by very low risk of fire occurrence.

4. Discussion

Although fire is an intrinsic phenomenon within the savanna ecosystem, the understanding of the various factors driving the occurrence of vegetation fires is vital for sustainable fire management within ecosystems. The study reveals the utility of geospatial and earth observation tools in predicting and mapping the heterogeneity of fire occurrence as determined by fuel, topographic, climatic and anthropogenic factors. The study also determined the contribution of the various predictor variables to fire occurrence. Findings from the study have revealed that the variability in fire occurrence can be effectively predicted using fuel, topographic, climatic and anthropogenic factors in a Maxent environment with a satisfactory accuracy of 0.77 (Lissovsky and Dudov, 2021).

The study findings greatly show the utility of the widely used Maxent as a rigorous fire prediction model. Fire occurrence data is generally presented as presence-only data and Maxent is highly suitable for handling such data (Mlambo et al., 2024). The strength of the method utilized in the study is that we managed to exclude highly correlated predictor variables from the model fitting which greatly improved the model performance (Dormann et al., 2013). This key step removes mutually dependent predictor variables from other model inputs. The multicollinearity test revealed that 11 out of 23 predictor variables, shown in Table 2, were not collinear and were therefore the best set of variables to be used in predicting the occurrence of vegetation fires using the Maxent model. The excluded variables were considered to be useful but similar information was contained in other variables.

Fire occurrence is greatly influenced by topographic, vegetation, climatic and anthropogenic characteristics of a landscape. Topographic and climatic conditions which influence fuel load were the major contributing variables towards fire occurrence. A higher probability of fire occurrence characterizes areas with higher precipitation and temperature. Fires have been observed to occur largely in areas of precipitation ranging between 500 mm and 700 mm (Archibald et al., 2010b). While high precipitation influences the level of fuel moisture during the fire season thereby decreasing fire ignition probability, high precipitation levels promote the accumulation of biomass during the pre-fire season which increases the likelihood of burning during the fire season (Guo et al., 2017). The research findings are not surprising because Makhaya et al. (2022) in KwaZulu Natal, South Africa also indicated that a correlation between rainfall and temperature affects biomass and hence fuel characteristics which generally influence the occurrence of vegetation fires. The study findings also align with findings by Guo et al. (2017) where the temperature was also an important factor in influencing fire occurrence by increasing evaporation from vegetation and decreasing the moisture content of potential fire fuels.

Additionally, the observation of the association between elevation and fire occurrence agrees with findings from several studies (Guo et al., 2017; Mishra et al., 2023; Mupfiga et al., 2022) where fire occurrence was high in regions of higher elevation. Contrary to a study by Guo et al. (2017), in this study, high fire risk was associated with areas of higher elevation. The eastern regions characterized by high elevation and exotic forest plantations were also predicted as having a high risk of fire occurrence. This observation agrees with previous studies (Makhaya et al., 2022; Mpakairi et al., 2018; Mupfiga et al., 2022; Strydom and Savage, 2016) where fire occurrence was observed to be highly correlated with elevation where there is an association between higher elevation and higher probability of fire occurrence (Graham et al., 2023). The research findings are not surprising because topographic factors such as elevation determine the local climate variations, especially the spatial distribution of precipitation and temperature, hence, controlling fuel type

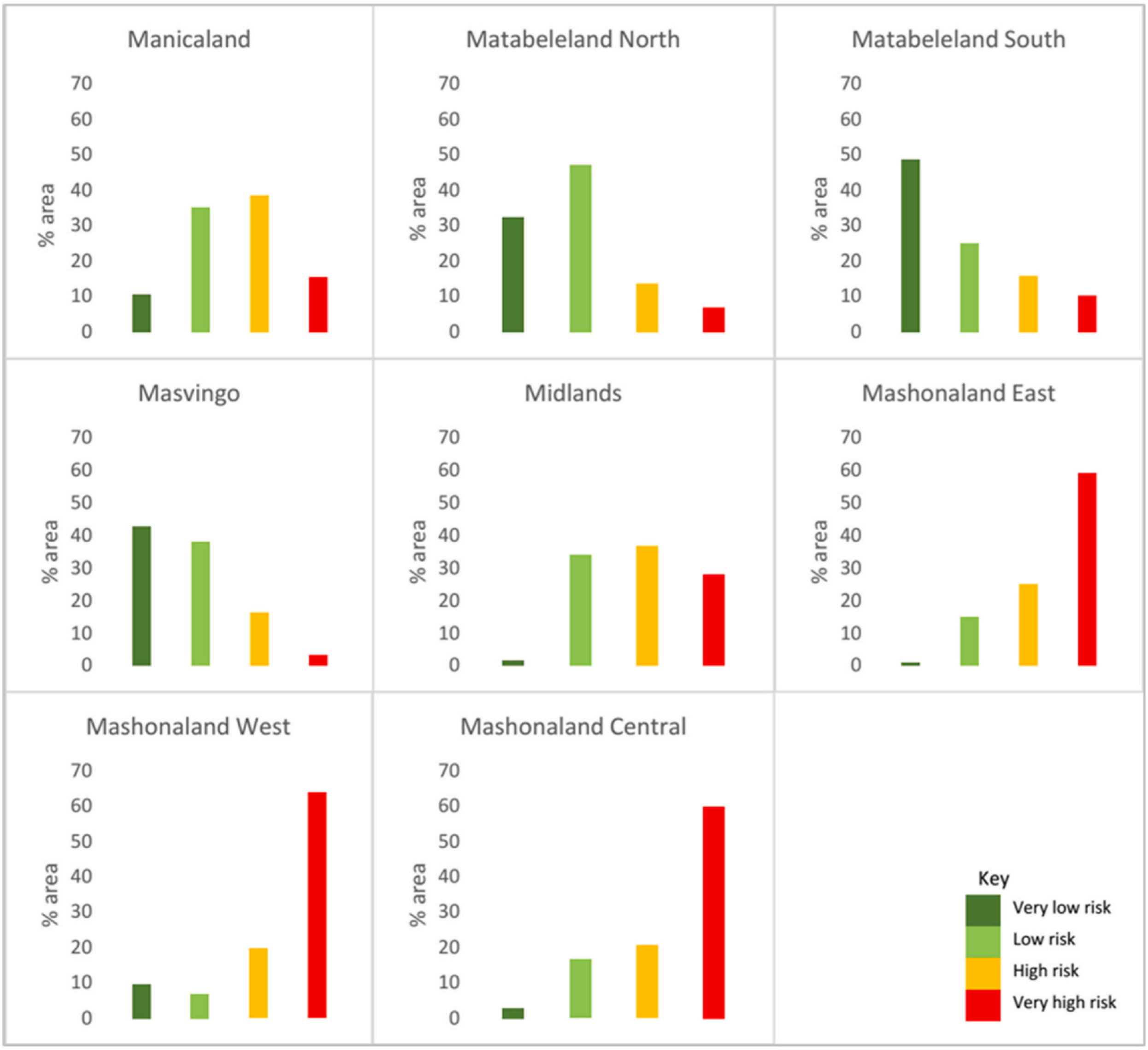

Fig. 7. Graphs showing the percentage level of the fire risk for each province.

distribution and flammability (Graham et al., 2023; Zhang et al., 2017).

The human footprint variable was utilized in this study as a proxy for the contribution of human activities to vegetation fire occurrence. This anthropogenic data set was developed based on overlaying eight factors, built-up environment, population density, pasture land, croplands, railways, roads, waterways and electric infrastructure. The combination of all these factors makes the human footprint, a more robust measure of human activities. This predictor variable had a considerable contribution (16.4%) to fire occurrence, clearly showing the great contribution of human activities to the occurrence of vegetation fires in the study area. This agrees with previous research (Armenteras et al., 2013; Guo et al., 2017; Piralilou et al., 2022) where anthropogenic factors were highlighted as highly contributing to fire occurrence. Related studies have also emphasized that the likelihood of the occurrence of vegetation fires fire occurrence increases when there is access by human activities into a landscape (Guo et al., 2017; Piao et al., 2022). The strength of this research lies in the use of a more robust measure of human activities and their association with fire occurrence. This is also the first study in Zimbabwe which incorporates anthropogenic factors in modelling fire occurrence at a national scale.

The Normalized Difference Vegetation Index (NDVI), applied as a proxy for biomass, was utilized in the model as an indicator of the fuel amount and had low predictive power (2.6%). This finding is consistent with previous studies which indicated a lack of linear relationship between NDVI and fire occurrence in most ecoregions (Zhang et al., 2017). Research by Mishra et al. (2023) in Nepal, also highlighted that vegetation-related predictor variables had a lower contribution to fire occurrence. In a study by Guo et al., 2017, vegetation which had a positive influence on fire occurrence gives an indication of the available fuel for fire ignition.

Based on the Maxent probability modelling, the study findings show that the central, eastern and northern regions of Zimbabwe had a very high risk of fire occurrence. The northern and central regions of the study area are characterized by resettlement areas which are greatly associated with burning activities (Mupfiga et al., 2022). This region of high likelihood of fire occurrence also coincides with tobacco-producing farming areas where hard timber from the miombo woodlands is used for tobacco curing (Zinyowera et al., 2021). The southern region and western parts, characterized by protected areas such as Gonarezhou and Hwange National Parks, respectively, had a very low fire risk. Although these areas are characterized by high temperatures and high biomass content, protected areas are also associated with strict fire management strategies which minimize fire ignition as observed in the study (Guo et al., 2017).

The study findings contribute to the improved understanding of fire patterns and the drivers of fire occurrence. This valuable information assists fire managers and communities in decision-making related to fire management strategies. For sustainable fire management, the spatially varying fire risk zoning may result in the development of fire management strategies which are specific to local areas.

Although Maxent is a valuable model for predicting the occurrence of phenomena using presence-only data, the performance of Maxent is compromised because defining true fire absence during model fitting is difficult because fires do not always occur in every fire-prone area. This, therefore, implies that there are chances of classifying highly vulnerable areas as being of low risk to fire occurrence if no fire is detected in such areas (Mishra et al., 2023). Further studies should also assess the importance of predictor variables under varying conditions such as agroecological zones, seasons and vegetation types.

5. Conclusion

Uncontrolled fires disturb vegetation and can threaten biodiversity. This national-scale fire prediction study has unveiled the interaction between climatic, topographic, vegetation and anthropogenic variables to predict the potential fire vulnerability at a national scale in Zimbabwe using the maximum entropy method (Maxent). The model evaluation, with a good level of accuracy (AUC of 0.77), shows the utility of the Maxent model in predicting the probability of fire occurrence. The most important variables influencing the occurrence of vegetation fires in the study area included elevation, precipitation seasonality, temperature annual range and human footprint. The research findings are critical for understanding the major driving factors of vegetation fire occurrence in Zimbabwe and, hence, provide valuable information for the fire managers' decision-support system. The free availability of MODIS fire data enabled the cost-effective and reasonably accurate prediction of fire occurrence. The fire risk map is important for informing policy and management decisions related to forest fire prevention and management in Zimbabwe. The findings offer valuable insights into the fire vulnerability driving factors and the development of proactive measures to lower the risk of future fire outbreaks. Using the research findings, fire managers can identify fire-prone areas and appropriate measures can be implemented. This study highlights the valuable use of satellite fire data coupled with machine learning methods to predict the likelihood of vegetation fire occurrence which can inform policy and management decisions regarding fire prevention and management. The method can therefore be applied in other landscapes to avoid unnecessary environmental and socioeconomic losses related to fire occurrence.

CRediT authorship contribution statement

Upenyu Mupfiga: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Onisimo Mutanga:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Methodology, Investigation, Conceptualization. **Timothy Dube:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization.

Ethical statement

The authors of this manuscript declare that all ethical practices have been followed during the development, writing, and publication of the research reported in this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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